



Latent class and Latent Transition Analysis 2

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Including covariates in the latent class model.

Recall

We can generalise the notation of the latent class model. We replace O by y , and probabilities by density functions f .

$$\begin{aligned} L &= \prod_{i=1}^N p(O_i) \\ &= \prod_{i=1}^N \sum_{k=1}^K \pi(k) p(O_i | k) \\ &= \prod_{i=1}^N \sum_{k=1}^K \pi(k) \prod_{j=1}^J (p_{jk})^{O_{ij}} (1 - p_{jk})^{1 - O_{ij}} \end{aligned}$$

now becomes

$$\begin{aligned} L &= \prod_{i=1}^N f(y_i) \\ &= \prod_{i=1}^N \sum_{k=1}^K \pi(k) f(y_i | k) \\ &= \prod_{i=1}^N \sum_{k=1}^K \pi(k) \prod_{j=1}^J f(y_{ij} | k) \end{aligned}$$

We can add covariates in two places in the model.

- modelling the class sizes $\pi(k)$
- modelling the class profiles p_{jk} or the parameters of $f(y_{ij} | k)$

We focus on the first of these.

Treating covariates as inactive

The simplest approach is to carry out a latent class analysis and to examine the class assignments and their relation to covariates.

This can be done in two ways:

Hard assignment of cases. We assign each individual to a class, and then look at the relationship of class assignment to covariates.

Probabilistic assignment of cases. Rather than assigning each case absolutely to a class, we use the assignment probabilities w_{ij} and sum these over categories of the covariates.

Example - Crime and the neighbourhood.

Indicator analysis - 5 class solution. Does class membership depend on sex?

Hard assignment:

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	809.254 ^a	4	.000
Likelihood Ratio	842.925	4	.000
Linear-by-Linear Association	213.667	1	.000
N of Valid Cases	7168		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 147.99.

Cluster modal * Sex Crosstabulation

			Sex		Total
			Male	Female	
Cluster modal	1	Count	2143	1434	3577
		% within Sex	63.8%	37.6%	49.9%
	2	Count	391	1283	1674
		% within Sex	11.6%	33.7%	23.4%
	3	Count	460	484	944
		% within Sex	13.7%	12.7%	13.2%
	4	Count	209	107	316
		% within Sex	6.2%	2.8%	4.4%
	5	Count	154	503	657
		% within Sex	4.6%	13.2%	9.2%
Total		Count	3357	3811	7168
		% within Sex	100.0%	100.0%	100.0%

Could also assign individuals to classes only if probability reaches some threshold for some class.

Say $p=0.75$.

Probabilistic assignment

	Sex	
	Male	Female
	Sum	Sum
Cluster1	1937.64	1590.06
Cluster2	245.44	794.24
Cluster3	467.99	489.41
Cluster4	515.19	398.62
Cluster5	190.73	538.67

Covariate proportions

sex

Male	0.5772	0.0731	0.1394	0.1535	0.0568
Female	0.4172	0.2084	0.1284	0.1046	0.1414

Active covariates

Active covariates play a part in the latent class modelling. We model the class sizes through a multinomial logistic model:

$$\pi(k | x) = \frac{\exp\{\eta(k | x)\}}{\sum_k \exp\{\eta(k | x)\}}, \text{ where}$$

$\eta(k | x)$ = linear model involving effect of x

$$= \alpha_k + \beta_k x \text{ (main effects if } x \text{ continuous)}$$

$$= \alpha_k + \beta_{kx} \text{ (main effects if } x \text{ categorical)}$$

Can be easily extended to more than covariate.

Modelling results

number of classes	AIC	BIC	AIC3	L2	Df	p-value	classification errors
5	38817.9	39051.7	38851.9	31.27	29	0.35	0.291
5+sex	37808.3	38069.6	37854.3	112.32	88	0.04	0.250
6+sex	37796.1	38112.5	37842.1	84.19	80	0.35	0.163

Loss of 5 cases

5+age+sex	37122.4	37603.7	37192.4	925.8	1064	1.00	0.207
6+age+sex	37087.9	37679.3	37173.9	859.5	1048		0.192

Note that L^2 changes when covariates are added in to the model. The table formed is the cross-classification of all indicators together with the covariate categories.

To examine the importance of the covariates we look at AIC or BIC based on L and not L_G .

Despite loss of five cases, we note that BIC is a lot lower for age +sex model. (Strictly should now redo the results based on 7163 cases)
 BIC tells us that 5 class model is acceptable. AIC will require more classes.

Age and sex class proportions

Covariates	Class 1	Class 2	Class 3	Class 4	Class 5
sex					
Male	0.5542	0.0558	0.2353	0.1061	0.0486
Female	0.2756	0.2720	0.0890	0.1880	0.1753
agegrp					
16-19	0.3172	0.0568	0.2896	0.0707	0.2657
20-24	0.3168	0.0990	0.2933	0.0284	0.2626
25-34	0.4221	0.1509	0.2257	0.0014	0.1999
35-44	0.4306	0.1411	0.2127	0.0849	0.1307
45-54	0.4722	0.0685	0.1802	0.1816	0.0975
55-64	0.4099	0.1019	0.1406	0.2599	0.0878
65-74	0.4166	0.2466	0.0630	0.1986	0.0752
75-84	0.3030	0.4243	0.0155	0.2312	0.0259
85 and over	0.1611	0.6052	0.0002	0.2324	0.0011

Note the increasing proportion of elderly respondents and the larger proportion of females in class 2 “problems at night”.

More complex example

The second example represents work in progress and relates to research being carried out at Lancaster by myself, Keith Soothill and Jiayi Liu.

It relates to changing criminal convictions over time among females.

This is perhaps becoming a moral panic.

SCOTSMAN article September 2006

VIOLENT crime committed by women has soared in Scotland, new statistics revealed yesterday.

More than 327 women committed non-sexual violent crimes, such as serious assaults and attempted murder, in 2004-5 - up almost 50 per cent in four years.

Criminologists yesterday blamed the increasing use of drugs, binge drinking and wider changes in society for women's increasing criminality.

"It's drink and girl-power. Everyone thinks of the Spice Girls being an empowering thing. Suddenly there is a collective view that girls are here to do everything they like, but unfortunately this also gives them the right to do stuff that is just as idiotic as men do."

Vince Egan, a forensic psychologist at Glasgow Caledonian University

Importance of age period cohort models

Why are we interested in separating out the effects of age, period and cohort?

This is important criminologically.

Are changing patterns of crime due to

- i. year by year effects which affect all ages equally (eg routine activity theory) - economic changes, govt policy changes, global and national events
- ii. Generational effects - each generation thinks anew about criminal activity based on unique experiences in childhood. Also Easterlin hypothesis related to cohort size affecting criminal behaviour. Delinquent generations.
- iii. Age. Well known age-crime relationship. Age effects thought of as biological or psychological but may also have interactions with year if government targets certain age groups with policy.

Note that this is a tricky problem statistically. Separation of age, period and cohort effects is difficult as $\text{period} = \text{cohort} + \text{age}$ - there is linear dependence.

Typologies of crime

This work means that we first need to engage in a long standing problem in criminology - that of classifying criminal behaviour

We adopt a developmental approach - can we instead identify **types of criminal activity** in **distinct age regions** of an individual's history? Classification of crime, not the criminal.

Allows the development of an offender from one crime type to another. Criminologically, follows approach of Sampson and Laub (1993, Harvard UP) of pathways through crime.

Typologies of crime

A simplified criminal history of a typical male offender is shown below:

age	14	17	20	22
Offences	Bicycle stealing	Shoplifting; Carrying offensive weapon	Fraud; Petty theft	Fraud; Petty theft; Receiving stolen property

We would like, for example, to determine whether **bicycle stealing** and **shoplifting** tend to co-occur in this cohort, whether **fraud** and **receiving stolen property** co-occur, and at what ages these offences are most prevalent.

Typically we do this by taking fixed age windows 10-15, 16-20, 21-25 etc and looking at offending within a window.

The Offenders Index data set

We use the **England and Wales Offenders Index** - a Home Office research data set, which is a court based record of the criminal histories of all offenders in England and Wales from 1963 to the current day.

The complete data set is rarely analysed. We analyse data from the Offenders Index Cohort study, taking six birth cohorts born in 1953, 1958, 1963, 1968, 1973, 1978 and followed through to 1999.

This **birth cohort** is an approximate **1 in 13 sample of all offenders born in these years**, and samples all offenders born in four selected weeks

The index stores dates of conviction, the offence code of the conviction (very detailed) and the disposal or sentence.

Official histories allow for large sample sizes.

Larger sample sizes are possible. Analysis based on arrests (US, German studies) or convictions (UK studies). However unconvicted offending is often not analysed.

Problems with the data set.

- ◆ It does not contain information on death, or immigration, or emigration. An individual might have left the country (perhaps to Scotland), but this would be viewed as a period of not offending in the dataset.
- ◆ The dataset is formed by **record matching**, taking court records and matching them on name and data of birth to form criminal histories. Although this procedure compares well with police records (Francis and Crosland, 2002; Home Office) it can introduce inaccuracies.
- ◆ It does not contain all offences, but only **standard list offences** - minor offending such as speeding and public order offences are omitted.
- ◆ Problem with all longitudinal datasets - new offences are passed into law, or become viewed as more or less serious (standard list offence changes over time) - view of seriousness changes over time. Dealt with **by removing** all offences which **become standard list** or **stop being standard list** over the 30 year period.

The 38 broad offence groups

1	Lethal violence (including attempts)	20	Theft (in a dwelling)
2	Violence	21	Theft (machines/meters/electricity)
3	Firearms/dangerous weapon (possession etc)	22	Theft from vehicles
4	Resisting arrest etc	23	Theft of vehicles
5	Kidnapping/false imprisonment	24	Attempted theft of/from vehicle
6	Sexual 16+	25	Shoplifting
7	Sexual under 16	26	Fraud and forgery
8	Sexual consensual	27	Receiving and handling
9	Prostitution	28	Criminal damage
10	Burglary (dwelling)	29	Drugs (possession etc only)
11	Aggravated burglary (dwelling, other)	30	Drugs (supply, including possession with intent)
12	Burglary (other)	31	Drugs (import/export/production)
13	Going equipped	32	Absconding/bail/breach offences
14	Robbery	33	Public order
15	Blackmail	34	Perjury/attempting to pervert course of justice
16	Vehicle taking (aggravated etc)	35	Dangerous Driving
17	Theft	36	Immigration
18	Theft from person	37	Child cruelty etc
19	Theft by employee	38	Other

Methodology

Latent class approach based on binary indicators on 38 broad offence groups within five year age windows. Six birth cohorts 1953, 1958, 1963, 1968, 1973, 1978.

Latent class analysis estimates characteristics of offence classes that co-occur

Define set of indicator variables within the an age window.

$O_{ij} = 1$ if offender i is convicted for offence j

$O_{ij} = 0$ otherwise.

	<i>Age windows</i>							<i>No. of offenders in cohort</i>
<i>Birth Cohort</i>	<i>10-15</i>	<i>16-20</i>	<i>21-25</i>	<i>26-30</i>	<i>31-35</i>	<i>36-40</i>	<i>41-45</i>	<i>Male - female</i>
<i>1953</i>				<i>1979-1984</i>				<i>8851 - 2217</i>
<i>1958</i>			<i>1979-1984</i>					<i>9233 - 2348</i>
<i>1963</i>		<i>1979-1984</i>						<i>10686 - 2569</i>
<i>1968</i>	<i>1979-1984</i>							<i>9126 - 1797</i>
<i>1973</i>								<i>6118 - 1071</i>
<i>1978</i>								<i>3726 - 665</i>
								<i>47440 - 10667</i>

58,407 offenders in total.

Latent Class Analysis

We define O_i to be the prevalence vector for offender i over the 38 broad offence groups within each age group and each cohort.

Each observation is a collection of person-age-windows.
We remove age-windows which have no convictions.

Extension to age period cohort models

We extend the latent class model to include covariates in the latent class model. Each person-age strip belongs to a particular cohort c , a particular age group a and a particular year period p .

We allow the proportions of the sample in latent class k - $\pi(k)$ - also now to depend on a, p , and c . $\pi(k | a, p, c)$

We use a **multinomial** model to estimate parameters for each latent class.

$$\pi(k | a, p, c) = \frac{\exp\{\eta(k | a, p, c)\}}{\sum_k \exp\{\eta(k | a, p, c)\}}, \text{ where}$$

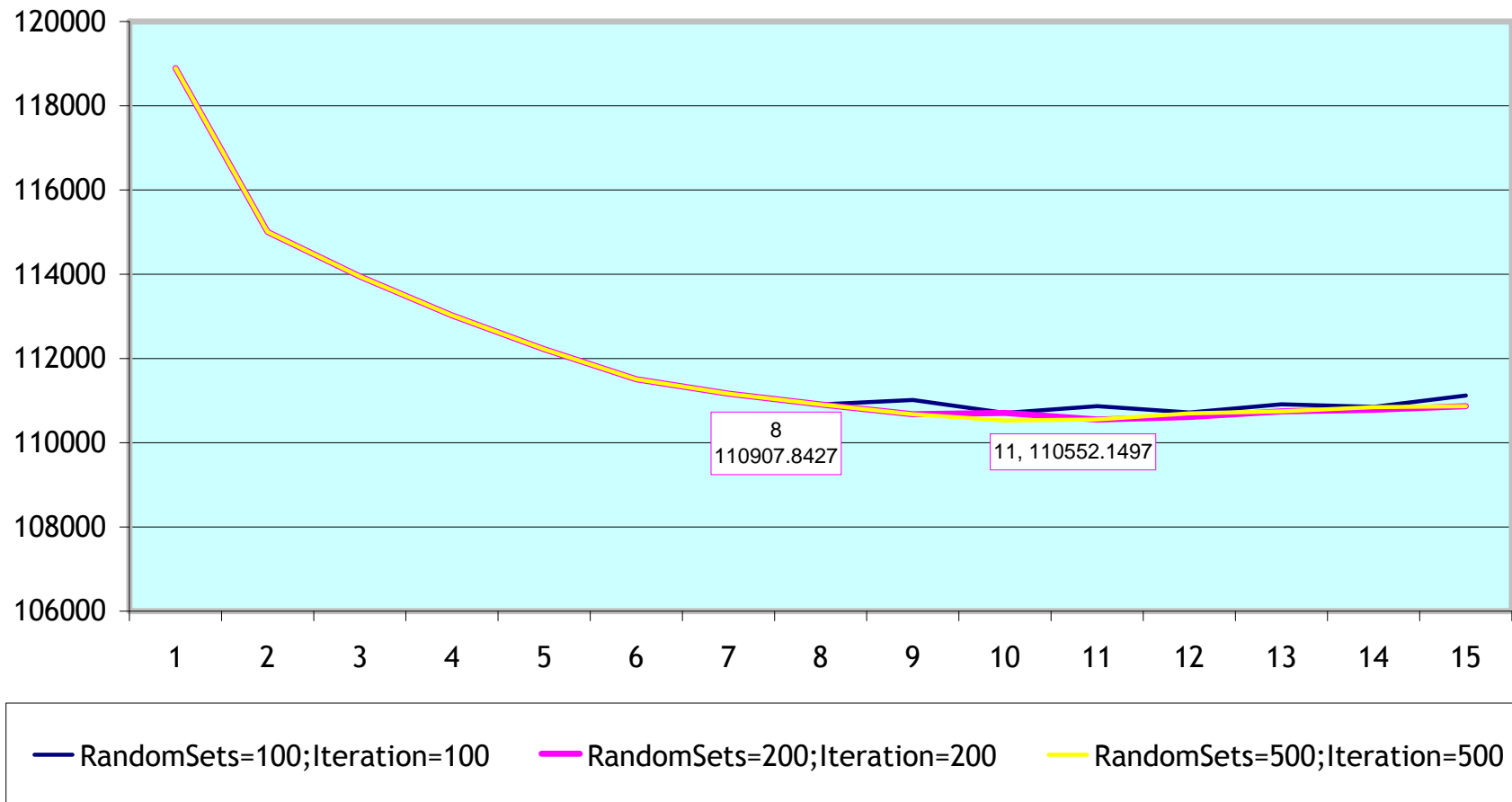
$$\begin{aligned} \eta(k | a, p, c) &= \text{linear model involving age, period and cohort effects} \\ &= \alpha_k + \beta_{ka} + \beta_{kp} + \beta_{kc} \text{ (main effects – one possible model)} \end{aligned}$$

We look at female data in this initial investigation as sample size is smaller.

Results of full data

We carry out an initial investigation using a no covariate model.

BIC: Latent class Analysis from 1 class to 15 classes



It suggested that 11 (or possibly 12) classes were needed.

Results 2

BIC values for latent class APC models

	BIC 11 classes	Number of parameters	BIC 12 classes	Number of parameters
“all interactions” cell model	110533.51	738	110553.86	808
age year and cohort	109501.20	608	109412.63	665
age and year	109071.50	558	109124.18	610
age and cohort	109063.47	538	108932.36	558
cohort and year	109301.99	548	109320.05	599
Age	109618.70	488	109675.27	533
Year	109506.85	498	109477.04	544
Cohort	110210.38	478	110156.74	522
None	110594.98	428	110717.40	467

Then complex strategy adopted to fit all latent class model with a different covariate set. This identifies the lowest value of BIC with the 12 class model with age and cohort (not year) as significant covariates. Other strategies are possible.

AGE+COHORT model

This suggests that the proportions of different typologies vary by age and by cohort but not by year,

We look at the class profiles to examine what these typologies are, and then examine the changing proportions of specific classes and how they change over age and time.

The 12 class solution for female offenders.

We look at the probabilities of observing a conviction in an age strip given cluster membership.

Class 2 has a very high probability for fraud and forgery (0.9999) and lower but still substantial probabilities for theft (0.22) and receiving and handling (0.25). All other probabilities are below 0.2. We label this “**Fraud with theft and receiving**”.

Six specialist single offence classes: Shoplifting (29%) Theft (9.7%) Violence (7.7%) Criminal damage (5.4%) Theft from meters (1.7%) drugs possession (3.9%)

Three paired offence classes: resisting arrest and absconding/bail offences (7.1%) receiving and handling with some shoplifting (4.4%) Theft by employee with some fraud (2.8%)

Three ‘versatile’ classes Fraud with theft and receiving (12.7%) Theft with burglary and shoplifting (acquisitive non-violent - 9.0%) and violent acquisitive (shoplifting, theft with some violence - 6.6%).

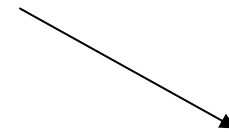


Changing proportions of the violence only female offending group.

We use the all-interactions model - a separate estimate of $\pi(k)$ for each cell.

Age cohort	11-15	16-20	21-25	26-30	31-35	36-40	41-45
1978	0.29	0.18	0.13				
1973	0.18	0.13	0.09	0.00			
1968	0.15	0.07	0.09	0.11	0.07		
1963	0.07	0.05	0.05	0.07	0.14	0.16	
1958	0.07	0.06	0.06	0.04	0.05	0.13	0.09
1953	0.02	0.02	0.04	0.03	0.05	0.0	0.15

Year effects will be diagonal effects in this table:

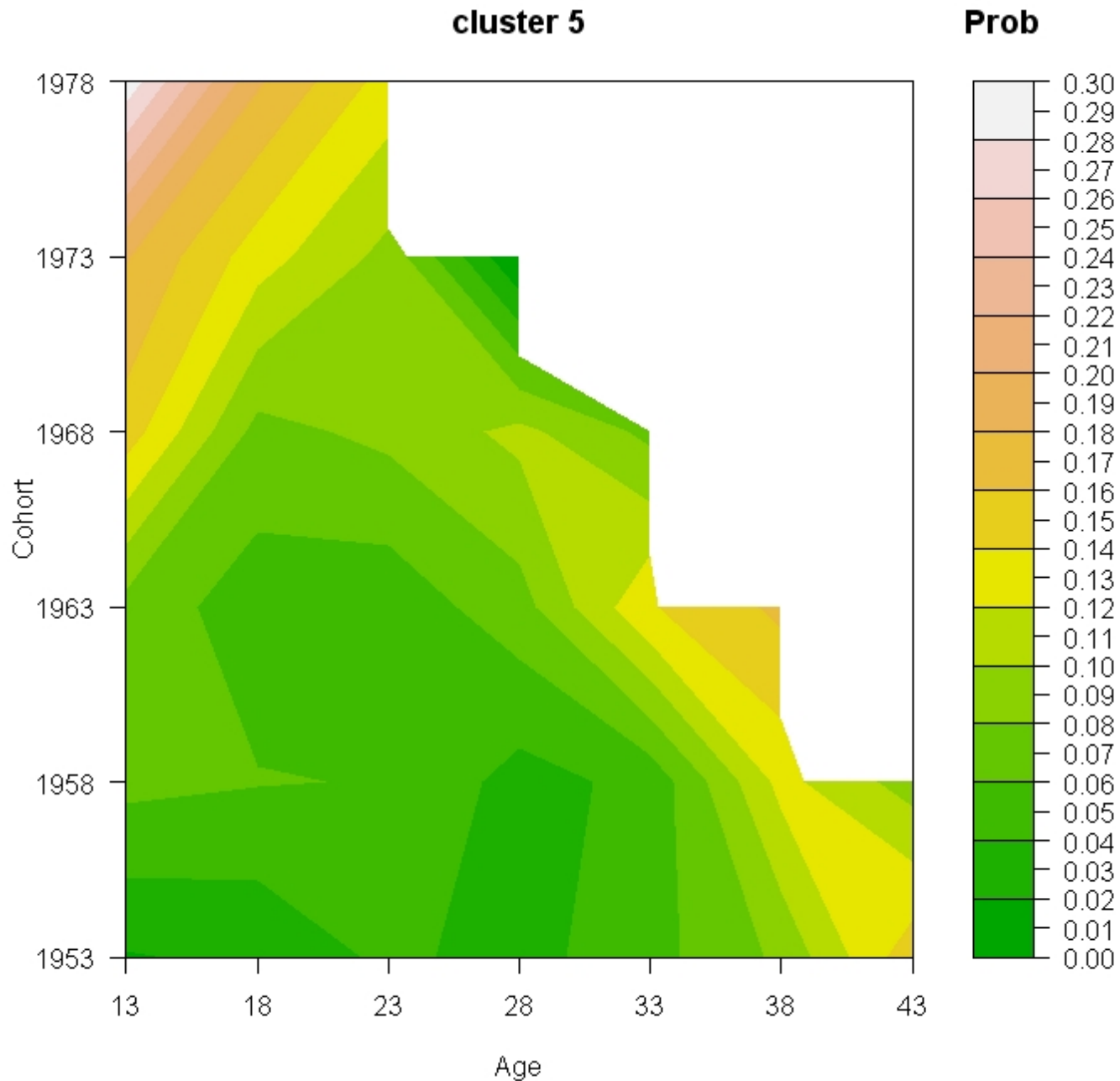


Cell entries are the probability of being in the female violence only class for different birth years and ages given a court conviction in that time period.

We can also plot this as a contour plot:



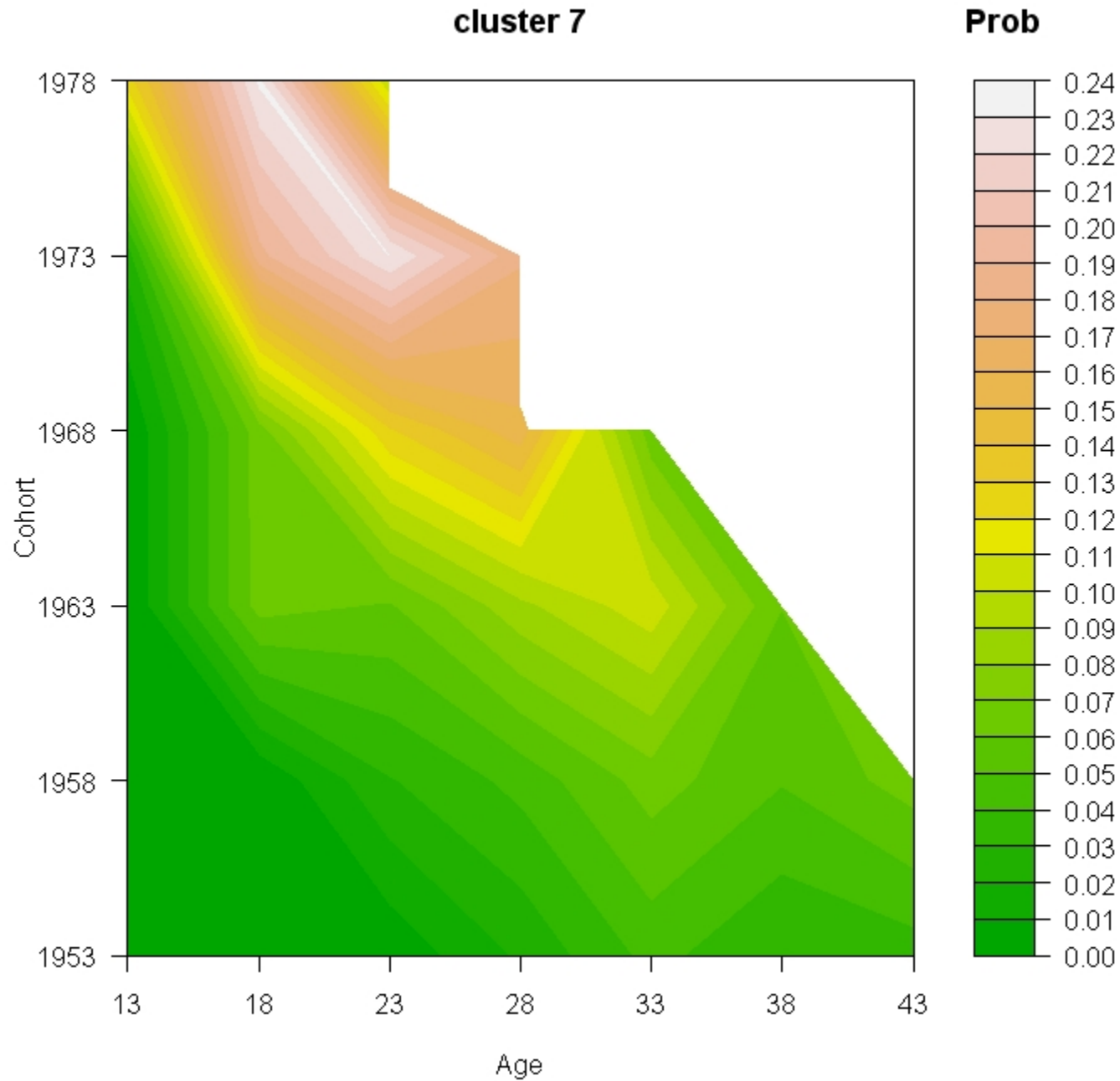
Violence only female offending cluster.



Two effects can be seen - increase in the proportion of young violence only convictions in recent cohorts.

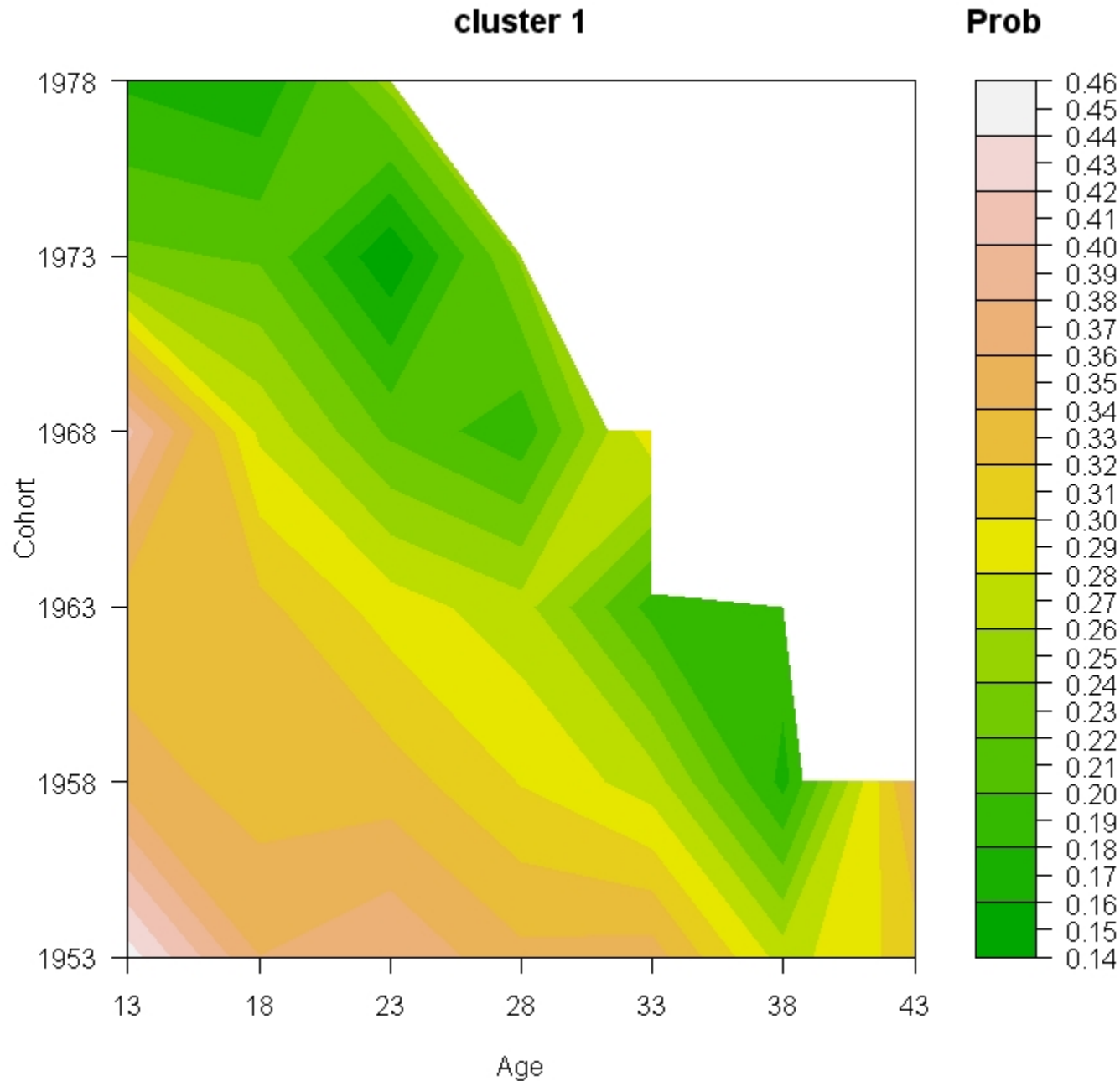
Also increase for older females in early cohorts/

Violent acquisitive (shoplifting, theft with some violence - 6.6%).



Some evidence of a year effect in later cohorts. Early 1990s.

Shoplifting only cluster



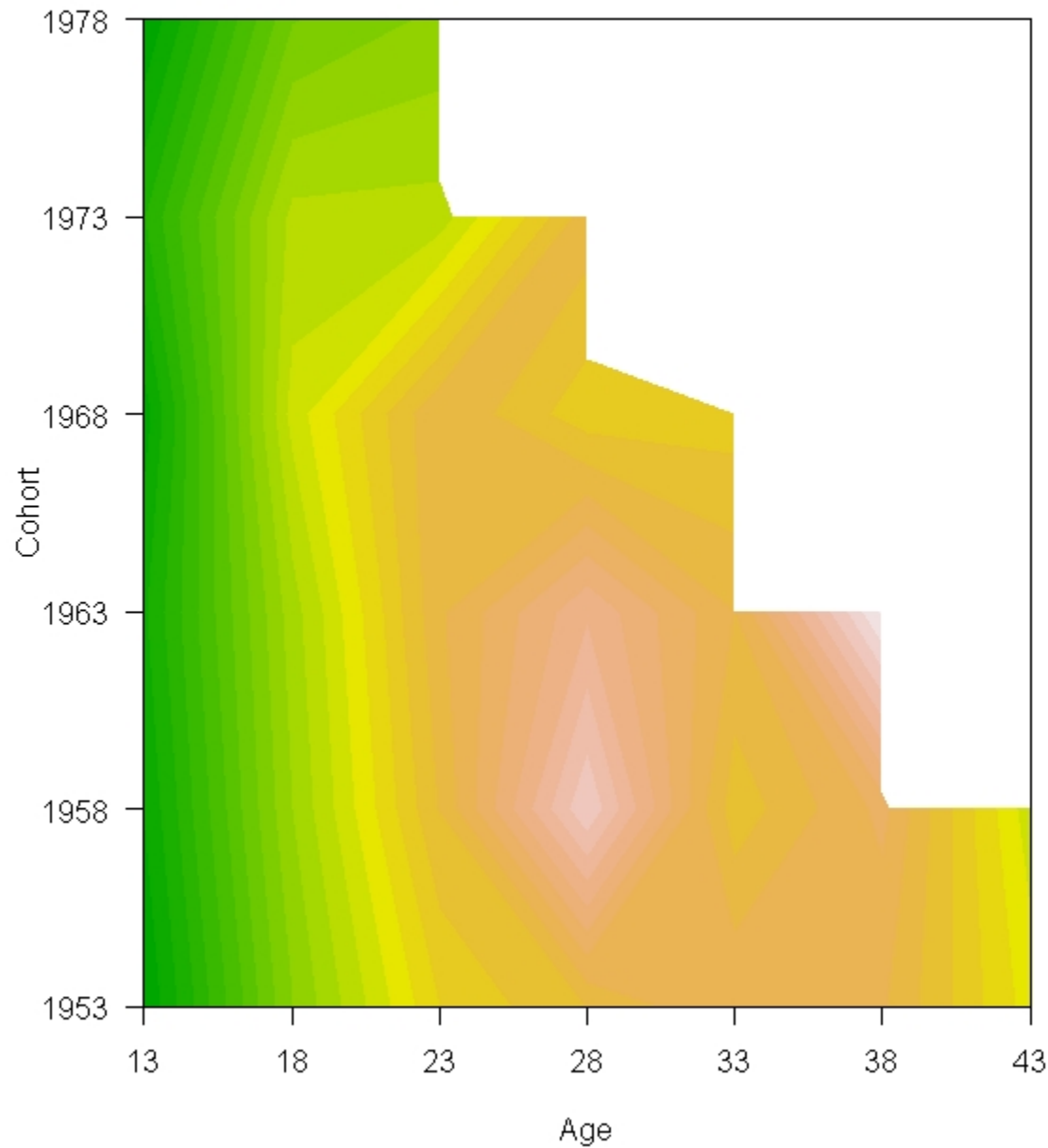
Complex pattern of effects. For 1953 cohort, proportion of shoplifters is nearly constant.

Most recent cohorts show a constant lower proportion.

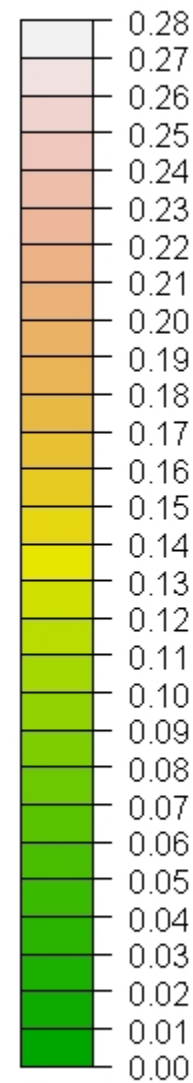
There is a declining age trend for middle cohorts.

Fraud with theft and receiving

cluster 2

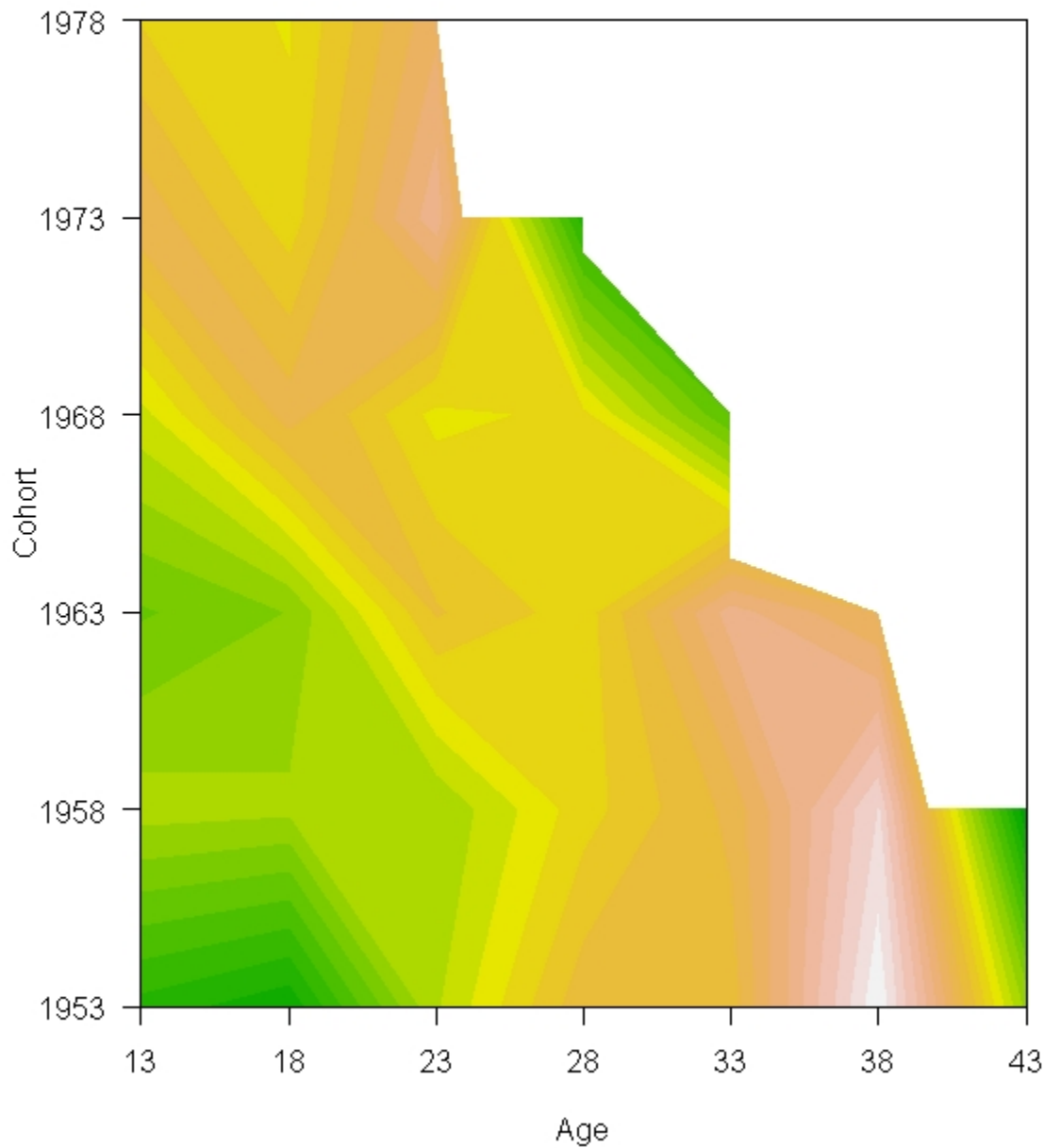


Prob

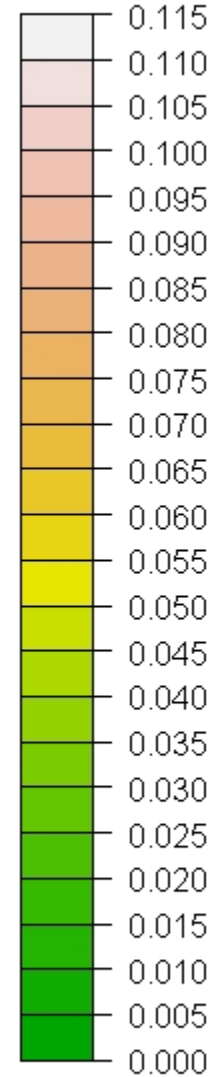


Strong age effect for fraud/theft group peaking in 26-30 group.

cluster 8



Prob



Criminal damage has strong year effect. Early 1990s shows peak which may have started to decline.



Criminological results

Methodology can give real insight into changes in the proportion of convictions across different typologies of crime

It is important to remember that the figures represent system changes as well as social change. Thus for minor offences, young people are diverted away from the court system into cautioning for later cohorts.

Proportions are not numbers of offenders - the number of females convicted of a crime are declining in the most recent cohorts in our study.

In general, a picture of increasing violence and increasing versatility in female convictions.

Discussion

- There is graphical evidence of different changes in different criminal typologies. Some effects change by year, others are cohort based. Need to consider more complex models with different subsets of age, period and cohort effects for each typology.
- Choice between using age, period and cohort as active variables (regression parameters co-estimated with latent class parameters) or inactive (where we estimate a latent class model without covariates and examine the proportion of cases in each age-period cohort combination at a second stage. Active is more correct, but needs substantially more computing time.
- Perhaps need to omit 10-15 age category from analysis as this is age group most affected by cautioning policy changes.
- Need to analyse male data
- More and better datasets needed to look at long term self report data.

Examining change over time

Latent class analysis with covariates (just discussed)

Repeated measures Latent Class Analysis

Latent Trajectory analysis

Latent transition analysis

Repeated measures Latent Class Analysis

This is similar to standard latent class analysis, but the indicator variables represent change over time on a small number of variables; it is most often used in panel surveys.

Eg Change in status of offending per survey wave
Change in self report offending and self report victimisation across waves.
Frequency of court appearances per year over a period

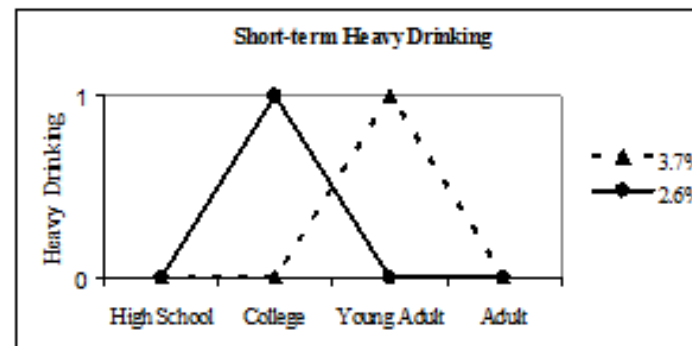
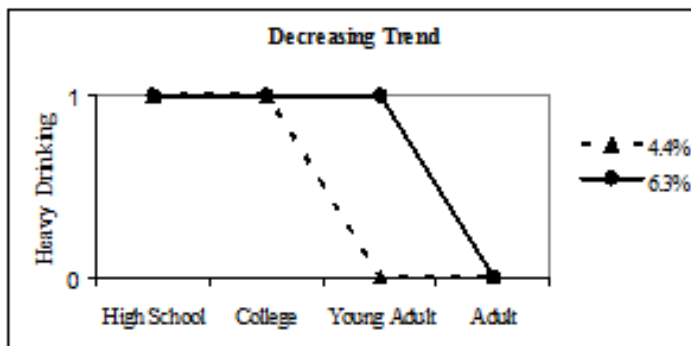
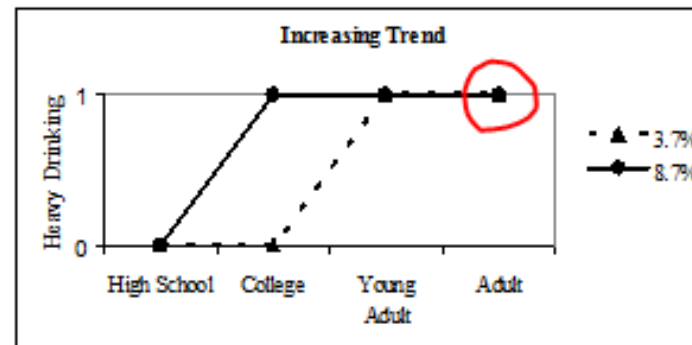
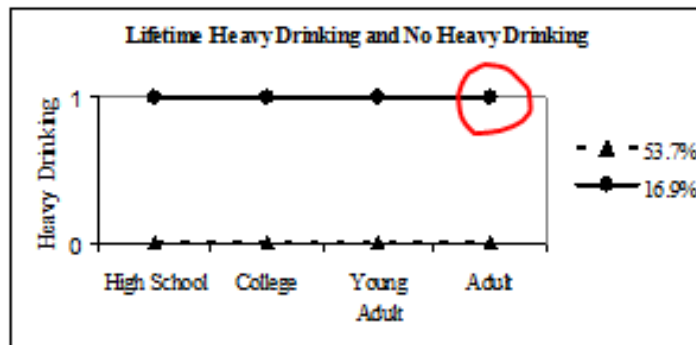
Four four time points and two variables, there would be eight response variables which would be represented as

V1T1 V1T2 V1T3 V1T4 V2T1 V2T2 V2T3 V2T4

A standard latent class analysis would then be carried out and the class profiles plotted for each variable by time.

Example - single variable "heavy drinking" by time. Eight latent classes found.
Taken from Lanza & Collins (2006), Journal of Studies on Alcohol

Question 1: Heavy drinking patterns



Latent trajectory modelling

This is similar to repeated measures latent class analysis, but the response over time is usually continuous and the curves are constrained to be smooth, normally by fitting a cubic curve to each class over time.

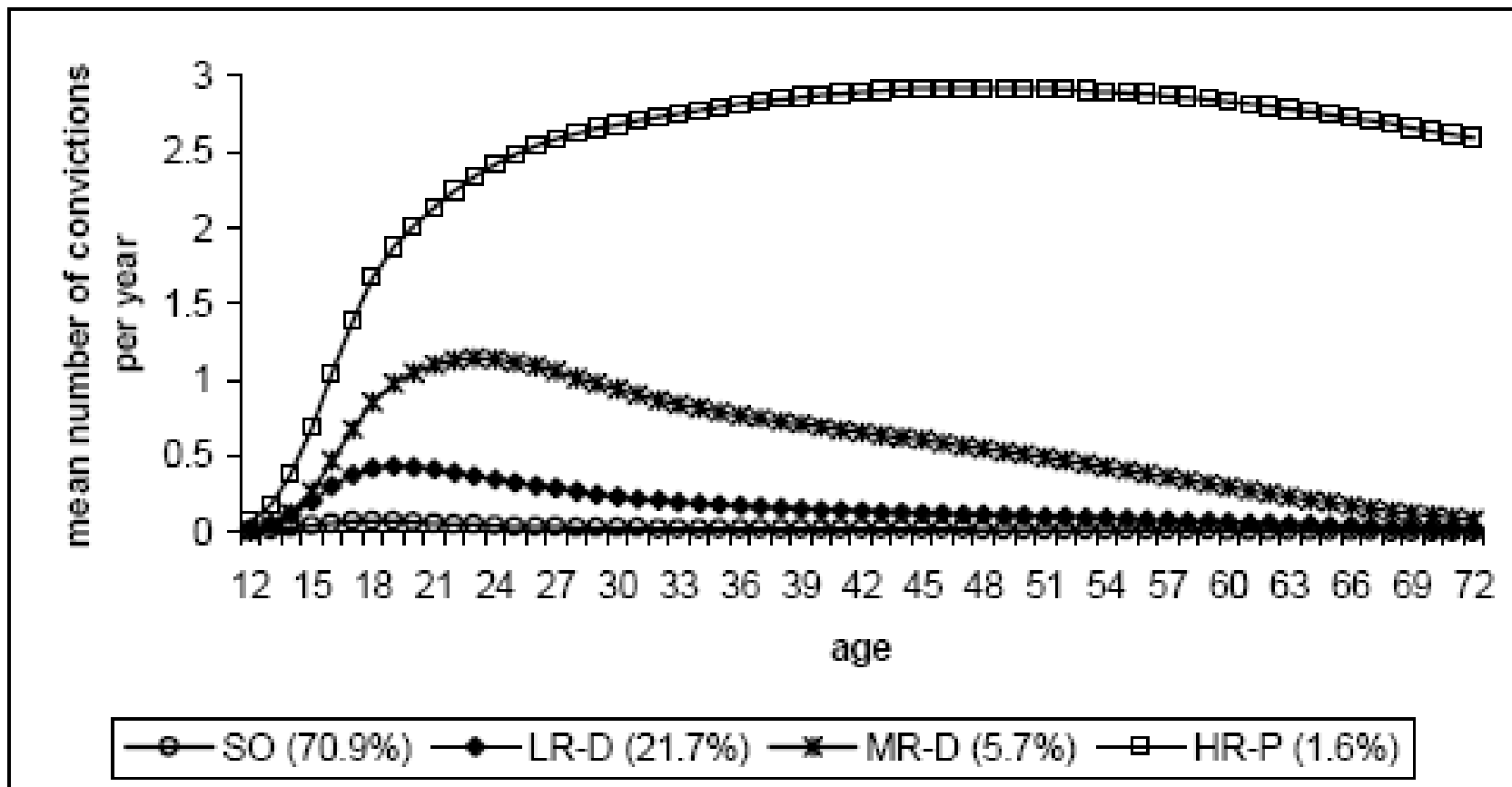
Specialist routines exist to fit latent trajectory models

PROC TRAJ in SPSS

Latent Class Growth Analysis in MPLUS.

Eg Criminal convictions in the US

Figure 2. Estimated Trajectories for Four-group Model



LR-D is low-rate desistance SO- single offence in adolescence
HR-P is High-rate persistent

Eg Criminal convictions in the UK

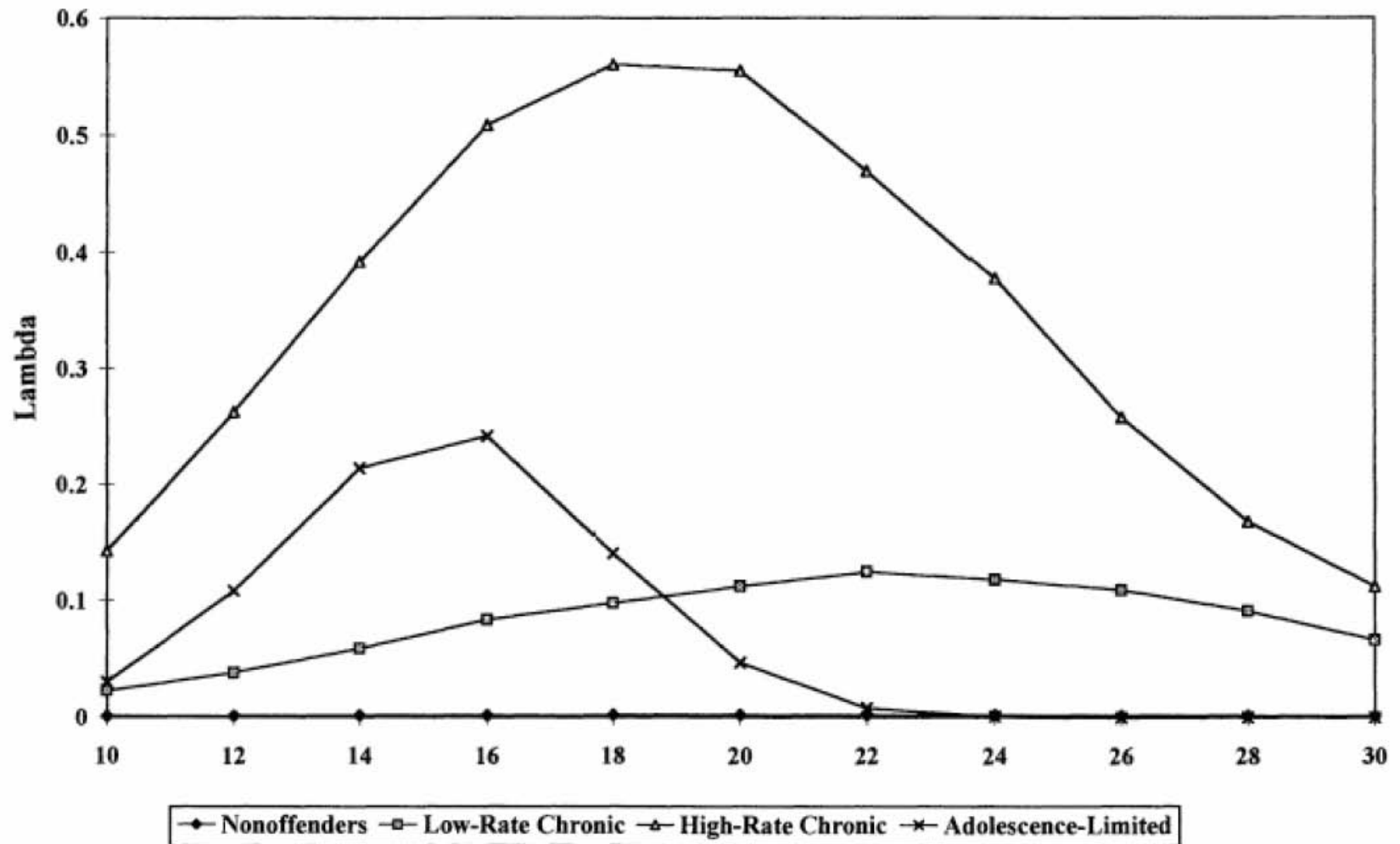


FIG. 1.—Predicted conviction rates by age for the London four-class model

Latent transition analysis

Latent transition analysis allows the estimation of transition matrices allowing individuals to move from one class to another over time.

In general, the latent classes stay constant in terms of their definition over time.

The transition matrices allow an insight into which classes are likely to transit into other classes as an individual ages.

Unlike latent trajectory analysis, the classes are not fixed paths, but a variety of different pathways with varying probabilities.

Transitions in offending

Early work by Stander et al(1989) looked at transitions between convictions, identifying the nature of a conviction by its principal or most serious offence.

1st conviction ->2nd conviction -> 3rd conviction etc

Not satisfactory, as

- *transitions are likely to be associated with age*
- *the time difference between convictions varies between individuals.*
- *Classifying a conviction by its principal offence loses information*

We instead want to work on transitions between latent classes at fixed age points.

We want to estimate the probabilities of changing latent classes as they proceed in their criminal career.

The transition matrix- invented data

Transition matrix with five latent classes based on age groups and latent classes.

		Age 21-25				
		1	2	3	4	5
Age 16-20	1	0.80	0.05	0.05	0.05	0.05
	2	0.20	0.40	0.20	0.10	0.10
	3	0.10	0.20	0.50	0.10	0.10
	4	0.07	0.02	0.01	0.30	0.60
	5	0.05	0.05	0.05	0.05	0.80

To estimate transitions, we can approach this problem in two ways.

Examining transitions between age groups(1).

1. We can fit a standard latent class model, treating all age strips as independent. We can then estimate transitions between classes by examining the assigned class for each age strip within a person, and looking at the observed class trajectory for that person across age strips.

Thus a female offender might have trajectory

Age group	10-15	16-20	21-25	26-30
Assigned class	1 ->	1 ->	3 ->	2

Summing over all cases for each transition gives an empirical estimate of the number of cases making each transition.

This treats the transitions as inactive - they are estimated later.

(also more complex procedure using estimated probs of individual class membership directly).

Examining transitions between age groups(2).

An alternative is **latent transition analysis**. Here we estimate the transitions as additional parameters. The number of parameters increases and models are more difficult to fit. Different transition matrices can be estimated for each distinct stage in time.

The latent classes can also be **dynamic** - with changing definition over time - or **static** (also known as measurement invariance). The first of these are difficult to estimate.

Latent transition analysis has been used a lot in addiction and substance abuse studies but has not been much used in criminology.

However - some recent papers on LTA in this area are:

- Lanza et al (2005) Psych. Methods (offending and substance use)
- Bartolucci et al (2007) J Royal Statist Soc. Series A (offending transitions)

Software- PROC LTA in SAS - download from Methodology Centre Penn State
MPLUS

The data

We initially look at two time points with the female conviction data. One transition at age 20.

Birth Cohort	Age						No. of offenders in cohort	
	10-15	16-20	21-25	26-30	31-35	36-40	41-45	Male - female
1953								8851 - 2217
1958								9233 - 2348
1963								10686 - 2569
1968								9126 - 1797
1973								6118 - 1071
1978								3726 - 665
No. of offenders in age group		26797	18,074					47440 - 10667
Male - female		-	-					4659 3,132

Modelling transition probabilities - Latent transition analysis

We represent the offending history of an individual i in time period a by a series of binary indicator variables $O_{ia}=(O_{ia1},\dots,O_{iaJ})$ where there are J offence groups.

We assume local independence

As before, $\phi_{O_{ia}|k_{ia}}$ is the probability of O_{ia} given K_{ia}

$$\phi_{O_{ia}|k_{ia}} = \prod_j (p_{jk})^{O_{ija}} (1-p_{jk})^{1-O_{ija}}$$

p_{jk} is the probability that a member of latent class k is convicted of offence j .

Then the joint distribution of the complete time sequence of the offences for individual i is $\{O_{ij}\} = P(O_{i1},\dots,O_{ia},\dots,O_{iA})$ is

$$\sum_{k_1} \phi_{O_{i1}|k_{i1}} \pi_{k_1} \sum_{k_2} \phi_{O_{i2}|k_{i2}} \pi_{k_2|k_1} \sum_{k_3} \phi_{O_{i3}|k_{i3}} \pi_{k_3|k_2} \cdots \sum_{k_A} \phi_{O_{iA}|k_{iA}} \pi_{k_A|k_{A-1}}$$

The likelihood L is the product of these quantities over all individuals.

Some initial LTA models

Models fitted using Proc LTA in SAS (Collins, Lanza, 2007).

6,464 female offenders in analysis.

We take ten of the 38 offence categories as the earlier analysis suggested these were most informative for female offending.

A characteristic of all latent class models is that there are multiple “local” maxima of the likelihood. This means that we need to be careful to hit the correct solution. LTA will be worse than LCA in this aspect.

LTA fitted repeatedly (50 times) with random start values. How well can the models be identified and fitted?

Three latent classes+transition: Four distinct solutions with different parameter estimates and BIC values. Best solution occurs in 60% of cases

Four latent classes+transition: 14 different solutions with different parameter estimates. Best solution occurs in 46% of cases.

Example of Proc LTA use

```
TITLE1 'LTA Model, 4 Statuses random Starting Values';
NSTATUS 4;
NTIMES 2;
ITEMS off2a off17a off19a off21a off25a off26a off27a
      off28a off29a off32a
      off2b off17b off19b off21b off25b off26b off27b
      off28b off29b off32b;
CATEGORIES 2 2 2 2 2 2 2 2 2 2;
MEASUREMENT TIME;
SEED 88888888888888;
RUN;
```

Variables are
time 1
offences
followed by
time 2

Best solution class profiles for four latent class LTA.

Cluster name	Versatile / frequent	Non-offending	Shoplifting	Theft/Fraud and forgery
Violence	0.20			0.13
Theft	0.44			0.25
Theft by employee				
Shoplifting	0.66		1.00	
Fraud and forgery	0.45			0.24
Receiving and handling	0.35			0.12
Criminal damage	0.18			
Absconding/bail/breach	0.14			
Drugs possession	0.36			

Female transitions given any convictions aged 16-25

Age 21-25

		Versatile/ frequent	Non- offending	shoplifting	Theft/ fraud and forgery
Age 16-20	Versatile /frequent	0.60	0.28	0.05	0.07
	Non-offending	0.05	0.00	0.33	0.63
	Shoplifting	0.03	0.91	0.05	0.01
	Theft/fraud and forgery	0.00	0.90	0.00	0.10

Latent class sizes at age 16-20: (π_1)

Versatile /frequent	6.3%
Non-offending	36.7%
shoplifting	21.3%
Theft/fraud and forgery	35.6%

Commentary

Very interesting - gives colour to latent trajectory concepts.

Adolescent limited

Shoplifters at 16-20 will most likely stop (90% chance) but have a one in ten chance of continuing.

Theft/fraud and forgery group are similar (90% chance of stopping) - but do not transit into other offending classes.

Chronic

Versatile/frequent will most likely continue in their own group (60% chance) but have a 28% chance of stopping.

Late starters

A late starter group will tend to join the theft/fraud latent class (63% chance) with only a 5% chance of becoming versatile.

TO END

Course on Latent class analysis at Lancaster!

End of September 2008. Prof Linda Collins, Methodology Centre, Penn State University. Only £120 for academics - £60 for students!

Get more detail and more insight.